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Is rapid recovery always the best recovery? - Developing a machine learning approach for optimal assignment rules under capacity constraints for knee replacement patients

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Abstract

Recent research suggests that rapid recovery after knee replacement is beneficial for all patients. Rapid recovery requires timely attention after surgery, yet staff resources are usually limited. Thus, patients with the highest possible health gains from rapid recovery should be identified with the objective to prioritise these patients when assigning rapid recovery capacities. We analyze the effect of optimal assignment rules under different capacity constraints for patients set on the rapid recovery care path using disease specific patient-reported outcomes (KOOS-PS) as measure for effectiveness. Subsequently, we build a policy tree to develop optimal treatment assignment rules. We use patient-reported and observational data from nine German hospitals from 2020/21. We apply a causal forest to estimate the double-robust treatment effects, controlling for patient characteristics. We confirm that on average, after controlling for patient characteristics, patients on the rapid recovery care path experience a significantly larger improvement of their joint functionality than patients on the conventional care path. Using the policy tree, we find that health outcome improvement can be increased on average from 17.87 (observed improvement) to 20.02 on the KOOS-PS scale $(0-100)$ without increasing capacity using optimal assignment rules selecting patients for rapid recovery with characteristics linked to higher health gains. Increasing the capacity expects an health outcome improvement of 20.13. We conclude that novel machine learning methods are effective in developing rules for selecting patients for rapid recovery based on their characteristics maximising overall health gains given limited resources. Ultimately, such algorithms should be used for clinical decision making systems as well as surgery and post-surgery capacity planning to work towards the pressing challenges of increasing demand and decreasing supply, driven by demographic change, in today's hospital sector.

1 Introduction

Rapid recovery after knee replacement has been the recommended protocol for knee osteoarthritis for more than ten years Pashikanti & Von Ah (2012). Early mobilisation is the key component for the rapid recovery care path, as it can improve health outcomes (Berg et al., 2018). Assignment to the rapid recovery care path requires patients to be mobilised less than 6 hours post-surgery; otherwise, patients are deemed to follow a conventional care path. The literature suggests that rapid recovery has several advantages: The main advantage is that it reduces the length of stay of patients. This can lead to less complications and hospital acquired conditions without increasing readmissions (Berg et al., 2018; Gromov et al., 2019). Additionally, a reduced length of stay contributes positively towards the mental state of a patient, as they return faster to their known surroundings (Winther et al., 2015; Machin et al., 2013). Moreover, other health care costs can be reduced Chua et al. (2020). Furthermore, the literature demonstrates that patients following the rapid recovery care path show better clinical outcomes and patient-reported outcomes compared to patients undergoing conventional care. (Berg et al., 2020) In addition, previous studies argue that early mobilisation is feasible and safe for all patient characteristics, which advocates that all patients could and should be set on the rapid recovery care path (Guerra et al., 2015). However, patients need to be mobilised in a time-frame when physiotherapists and nurses are available. This can be problematic outside of regular hospital business hours (Shaw et al., 2013). Therefore, mobilisation in the early evening, i.e. after 17:00 or 18:00 (and on weekends) is unlikely and surgeries for rapid recovery patients should not be scheduled in the afternoon. This limits the number of patients that can receive rapid recovery. Patients that receive the surgery too late in the afternoon must be set on the conventional care path and will most likely be mobilised the next day, i.e., after more than 6 hours. When a hospital needs to prioritise patients, it is thus crucial to understand which patients should be set on the rapid recovery care path and which on the conventional care path (Berg et al., 2018).

Building on this, we investigate two research questions: (1) Do patients on the rapid recovery care path have on average larger improvements than patients on the conventional care path? (2) What patients should be set on the rapid recovery care path given different capacity limits?

We exploit data from the German research project "PROMoting Quality" to investigate both research questions. We use the absolute change of the pre-surgery and 12-month post-surgery KOOS-PS as functional health outcome as our dependent variable (Meadows, 2011; Black, 2013). We use time to mobilisation post-surgery to identify rapid recovery patients. For the estimation of the average treatment effect of rapid recovery addressing the first research question, we use inverse probability weighting.

Investigating the second research question, we aim at maximising the average improvement patients receive from rapid recovery. Therefore, we systematically analyse heterogeneous treatment effects of the rapid recovery care path and identify patient characteristics that are related to a larger effect of rapid recovery. We are further interested in the effects after setting different capacity constraints appreciating that only a limited share of patients can be set on the rapid recovery care path. We use the causal forest, a newly developed causal machine-learning method by Wager & Athey (2018), to estimate heterogeneous effects. We then use the policy tree by Athey & Wager (2021) to find optimal assignment rules with and without a capacity constraint.

Over the last few years, optimal policy assignment methods evolved thanks to advances in machine learning. Optimal policy assignment methods maximise desired outcomes by exploiting treatment heterogeneity. In practical settings such as planning and scheduling of surgeries under capacity

constraints, optimal policy assignment can help decision makers to plan more efficiently. Based on the rapidly expanding literature started by Manski (2004) and developed further by Hirano & Porter (2009), Stoye (2009), Kitagawa & Tetenov (2018) developed a non-parametric solution for optimal treatment assignment with known propensities. In our setting the propensities are unknown. For that reason we follow Athey & Wager (2021). Athey & Wager (2021) suggests using a penalty term to reduce the share of treated patients. Our study showcases how a capacity constraint in the post-surgery care path affects the average outcome change of the patient sample and which patients should be set on the rapid recovery care path to maximise results. To the best of our knowledge, the methodology used in this paper has not been applied to post-surgery care paths of knee replacements. Additionally optimising under a capacity constraint is a novel approach.
The results of the analysis are relevant because they showcase how to increase health outcomes by selecting the patients which benefit most from rapid recovery. The developed policy tree could be used for optimizing the planning and scheduling of surgeries to select the right patients for rapid recovery maximising outcomes.

2 Data and Methods

In this section, we introduce the dataset, describe the empirical setup, present our method to estimate heterogeneous effects of the rapid recovery care path on the Knee Injury and Osteoarthritis Outcome Score (KOOS-PS[1]) change, and introduce our approach to building a policy tree for optimal treatment assignment under capacity constraints.

2.1 Data

To evaluate the effect of rapid recovery on joint functionality, we exploit data originating from the German research project PROMoting Quality (Kuklinski et al., 2020). In that project, a randomised controlled trial was conducted to investigate the effect of an alert one, three and six months post-surgery triggered if the health improvement of patients with primary hip and knee replacements was not as expected. Data from 3,110 knee replacement patients was collected from 2019 to 2020 from nine German hospitals. Due to an incomplete data set we excluded 550 cases, resulting in a final sample for our study of 2,560 observations.

Dependent Variable

The aim of this paper is to develop assignment rules maximising the improvement of patients' joint-related functionality after knee replacement. Therefore, our dependent variable is defined as the absolute change between pre-surgery (admission to the hospital) and 12-month post-surgery KOOS score (Roos et al., 1998; Roos & Lohmander, 2003). KOOS is a disease-specific PROM based on 7 items. The best achievable score is 0, where the patient has no pain and limitations (no impairment of functionality). At a score of 100, the patient has severe pain and vast limitations (full impairment of functionality). Therefore, a negative delta of the 12-month post-surgery vs. pre-surgery KOOS means a health outcome improvement. However, for ease of interpretation, in this study we switch the sign of the KOOS change, i.e., positive change is an improvement and negative change is a deterioration of joint functionality, as in Berg et al. (2020).

[1]PS refers to the version of the questionnaire with 7 elements. Henceforth we will refer to it as KOOS.

Independent Variables

Our independent variable of interest is whether a patient is on the rapid recovery pathway or on the conventional care pathway. The data includes information on when a patient was mobilised post-surgery in five bins, which are "mobilised in less than 6 hours", "mobilised between 6 and 12 hours", "mobilised between 12 and 24 hours", "mobilised between 24 and 48 hours", and "mobilised after 48 hours". We define the bin "mobilised in less than 6 hours" as corresponding to the patient being set on the rapid recovery path and the four other bins as the patient being set on the conventional care path. We use several variables from the PROMoting Quality dataset as control variables. The control variables consist of socio-demographic variables, medical variables, and variables related to the surgery. The socio-demographic variables include age, sex, living situation, job, job effort, and education. The medical information includes the pre-surgery KOOS score, height, weight, comorbidities, and pre-surgery hip and knee problems and treatments (prior congenital or developmental diseases, joint replacements, osteotomies, reconstruction, arthroscopic procedures, joint-related surgeries, joint-related pre-existing conditions). The variables related to the surgery include in which hospital the surgery was carried out, surgery duration, and surgical complications.

2.2 Methods

Setup and Identification

The average treatment effect (ATE) denotes the expected effect of the binary independent variable (treatment), in this case rapid recovery, on the outcome. Put differently, the average causal effect of the treatment is the difference between the potential outcomes, as introduced by the counterfactual framework of Rubin (1974), also called the Rubin Causal Model. In this framework, each individual has potential outcomes with and without treatment, denoted as $Y_i(d = 1)$ and $Y_i(d = 0)$ respectively, where d is a dummy for the treatment status. Formally, the ATE is defined as:

$$\tau = \mathbb{E}[Y_i(d = 1) - Y_i(d = 0)] \tag{1}$$

Additionally, conditional ATEs (CATE) are of interest for our analysis because they uncover heterogeneous treatment effects through conditioning on certain patient characteristics. Formally, the CATE is based on the ATE in Eq. 1, additionally conditioning on patient characteristics $X_i = x$:

$$\tau(x) = \mathbb{E}[Y_i(d = 1) - Y_i(d = 0)|X_i = x] \tag{2}$$

We can assume that the assignment of patients to the rapid recovery or conventional care path is not random and based on certain patient or provider characteristics. We use a strategy suitable for controlling for confounders by selection on observables. The required identifying assumptions for an observational study are (Wooldridge, 2010):

1. Conditional Independence Assumption (CIA): Random selection in the rapid recovery or conventional care path conditional on X:

$$Y_0, Y_1 \perp\!\!\!\perp d|X = x \tag{3}$$

2. Common Support (CS): Any unit (i.e., "patient" in the context of our study) could be observed with and without treatment:

$$0 < P(d = 1|X = x) < 1 \quad \forall x \in X \tag{4}$$

3. Exogeneity: The post-surgery care path does not affect the confounders in a way that is associated with the change of the KOOS:

$$X^d = X^{1-d} \tag{5}$$

4. Stable Unit Treatment Value Assumption (SUTVA):

    - The treatment state of one unit only influences its own outcome.
    - The treatment variation between units is minimal, meaning that the observed outcome of one patient in the treatment state corresponds to the potential outcome for all patients in that state.

It can be plausibly assumed that the CIA is fulfilled, as we control for various confounders. CIA could be violated if there were other unobserved patient characteristics relating to the patient's motivation to pursue the rapid recovery or the conventional care path. If patients with a higher motivation opt into rapid recovery and these patients additionally are more motivated in the rehabilitation program, those patients are most likely to have a higher improvement. This would then lead to biased (C)ATEs. We discuss this potential limitation in more detail section 4. According to CS, the probability of being on the rapid recovery care path for any observed combination of confounders and outcomes should be larger than 0 and smaller than 1. We check this assumption by plotting the density of propensity scores as suggested by Wager & Athey (2018).(see 6). Exogeneity can be reasonably assumed to be fulfilled because the confounders are observed at the admission to the hospital or during the surgery (complication and surgery duration), i.e before the care path is observed. SUTVA assumes that there are no spillover effects. It can be assumed that a patient on the rapid recovery care path will not affect the outcome of another patient. Since we can assume that all four identifying assumptions are fulfilled, we can identify the ATE and the CATEs.

ATE and CATE Estimation

The estimation of the ATE and the CATE is based on the augmented inverse-probability weighted scores by Robins et al. (1994) and the causal forest developed by Wager & Athey (2018), which is based on Breiman (2001). The (C)ATE can be estimated with Eq. 6.

$$\hat{\tau} = \frac{1}{n}\sum_{i=1}^{n}\hat{\Gamma}_i \tag{6}$$

$$\hat{\Gamma}_i = \hat{\mu}_{(1)}(X_i) - \hat{\mu}_{(0)}(X_i) + \frac{d_i}{\hat{e}(X_i)}\left(Y_i - \hat{\mu}_{(1)}(X_i)\right) - \frac{1-d_i}{1-\hat{e}(X_i)}\left(Y_i - \hat{\mu}_{(0)}(X_i)\right) \tag{7}$$

$\hat{\Gamma}_i$ consists of two components:

- The estimated conditional non-parametric expected values for the treated and non-treated group, $\hat{\mu}_{(1)}(X_i)$ and $\hat{\mu}_{(0)}(X_i)$.
- The estimated non-parametric propensity scores $\hat{e}(X_i)$, i.e. the probability that a patient will receive the treatment depending on the confounders.

Both components are estimated through the causal forest, for which we use the grf package in R by Athey et al. (2019).[2] The causal forest uses a random subsample of all confounders defined in section 2.1 for splitting the observation at a given node so that similar observations (observations with the same or similar confounders) end up in the same final leaf. As the causal forest is efficient in a high-dimensional setting, there is no need to pre-select confounders for model efficiency (Wager & Athey, 2018).

Policy Tree for Optimal Treatment Assignment with Capacity Constraint

In our setting we are not just interested in finding heterogeneous effects, but to find assignment rules that identify patients that benefit the most/least from rapid recovery. Based on the rapidly expanding literature on optimal treatment assignment started by Manski (2004) and developed further by Hirano & Porter (2009), Stoye (2009), Kitagawa & Tetenov (2018) developed a non-parametric solution for optimal policy assignment with known propensities. In our setting the propensities are unknown. For that reason we follow Athey & Wager (2021). We define the policy π as a function that maps X_p into $\{0,1\}$ as (Athey & Wager, 2021):

$$\begin{aligned} &\pi : X_p \rightarrow \{0,1\} \\ &X_p \subseteq X \end{aligned} \tag{8}$$

We want to build assignment rules based on patient characteristics that are known, when the post-surgery care path is scheduled. For that reason we exclude the hospital as a decision variable, as we want to find hospital independent assignment rules. Additionally, we also exclude complications and surgery duration as a decision variable, because complications and surgery duration is unknown at the point in time when patients are assigned to the rapid recovery care path[3]. Following Athey & Wager (2021) we exclude education for ethical and legal reasons. Discriminating based on education and other variables related to the socio-economic status should not effect the treatment assignment. To estimate the double-robust scores described above, we used among other variables BMI, weight and height. We exclude BMI as a decision variable in the policy tree, as it is an interaction between height and weight. Using height and weight should give more flexibility to the algorithm than only using the BMI as the algorithm is not limited on the functional form of the BMI. In other words, π sets patients based on their characteristics X_p on the rapid recovery care path or the conventional care path. X_p is the subset of the control variables, excluding the above mentioned variables. W is defined as the expected absolute change on the conventional care pare plus the expected CATE of patients that the policy π selects for the rapid recovery care path (cf. (Athey & Wager, 2021)). Therefore, $W(\pi)$ is the welfare[4] that policy π generates:

$$W(\pi) = \mathbb{E}[Y_i(\pi(X_i))] = \mathbb{E}[Y_i(0)] + \mathbb{E}[\tau(X_i)\pi(X_{p,i})] \tag{9}$$

[2] R: 4.1.3, grf: 2.2.1, Rcpp: 1.01.10

[3] Surgeons might have an expectation of the surgery duration based on potential risk factors (based on x-ray or CT Scans and patient characteristics

[4] As the dependent variable in our study is the change of pre- and post-surgery KOOS, welfare refers to the KOOS change.

This leads to the following maximisation problem, subject to a capacity constraint:

$$\begin{aligned} &\pi = \arg\max \{W(\pi) : \pi \in \Pi\} \\ &\text{s.t. } \frac{1}{n}\sum_{i=1}^{n} \pi(X_p) \leq Q \end{aligned} \tag{10}$$

$\pi \in \Pi$ requires that the Π is a pre-specified policy class. In our case, this means the decision tree must have a finite number of levels, to fulfill the assumption of finite Vapnik–Chervonenkis-dimensions. This means that the algorithm searches for a solution with a limited complexity, in this case the solution will be a decision tree with three levels. Infinite Vapnik–Chervonenkis-dimensions would make it impossible to find a solution. (Manski, 2004; Athey & Wager, 2021; Kitagawa & Tetenov, 2018)

The capacity constraint is fulfilled if the share of patients selected by π is smaller or equal to the capacity Q. Q is the share of patients that can be set on the rapid recovery care path and needs to be between 0 and 1. $Q = 1$ implies that there is no capacity constraint and potentially every patient could be selected for the rapid recovery care path. $\frac{1}{n}\sum(\pi = 1)$ implies that everyone gets set on the rapid recovery care path, thus resulting in the ATE. We assume that $Q < 1$. By setting Q equal to the share of patients on the rapid recovery care path in the sample, i.e., by keeping capacity constant, we are able to compare the welfare in the status quo with the welfare of the policy tree. Based on Chernozhukov et al. (2022) and Sverdrup et al. (2020) we can solve the maximisation problem from Eq. 10:

$$\pi = \arg\max \left\{ \frac{1}{n}\sum_{i=1}^{n}(2\pi(X_{p,i}) - 1(\hat{\Gamma}_i - C) : \pi \in \Pi \right\} \tag{11}$$

Where $\hat{\Gamma}_i$ are the double robust scores from Eq. 7. C is set as a sequence from the smallest individual treatment effect $\tau(x)_{min}$ to the largest individual treatment effect $\tau(x)_{max}$ and then solved iteratively to find what penalty C is required in order to fulfill the capacity constraint in Eq. 10 (Athey & Wager, 2021). The subsequent welfare generated by the policy π can be estimated as follows by the R package policytree by Sverdrup et al. (2020), which is incorporated in the grf package with Athey et al. (2019):

$$\hat{W}(\hat{\pi}) = \frac{1}{n}\sum_{i=1}^{n} \left\{ (2\hat{\pi}(X_{p,i} - 1)\hat{\Gamma}_i \right\} \tag{12}$$

3 Results

In the following section, we will first show summary statistics and the average treatment effect of the rapid recovery care path for patients with knee replacements[5]. Then, we will show the policy trees, their assignment rules and their corresponding effects (i.e., KOOS changes). We will show the results of policy trees without a capacity constraint and the empirical capacity constraint from the data.

[5] We additionally estimate the models for patients with hip replacements. The results are similar and can be received on request

Descriptive Statistics

Table 1: Descriptive Statistics - Relevant Variables

	Conventional Care N=1,365		**Rapid Recovery** N=1,195		
Dependent Variable					
KOOS change	16.98	(14.6)	17.08	(15.1)	
Socio-demographic Variables					
Gender					
Male	635	(46.52%)	555	(46.44%)	
Female	729	(53.41%)	631	(52.8%)	
Other	1	(0.07%)	9	(0.75%)	
Job effort					
I cannot judge that	130	(9.52%)	112	(9.37%)	
Predominantly sitting activities	512	(37.51%)	466	(39%)	
Light physical activities	237	(17.36%)	231	(19.33%)	
Medium-heavy physical activities	319	(23.37%)	264	(22.09%)	
Heavy physical activities	167	(12.23%)	122	(10.21%)	
Education					*
No school-leaving qualification	11	(0.81%)	1	(0.08%)	
Primary school	255	(18.68%)	184	(15.4%)	
Secondary school	804	(58.9%)	704	(58.91%)	
University	295	(21.61%)	306	(25.61%)	
Age	65.78	(9.1)	66.28	(9.57)	
Living situation					
Other	7	(0.51%)	10	(0.84%)	
I live alone	268	(19.63%)	204	(17.07%)	
I live in an institutional setting	13	(0.95%)	3	(0.25%)	
I live with my family	1,077	(78.9%)	978	(81.84%)	
Medical Variables					
Pre-surgery KOOS (0-100)	43.52	(12.95)	42.51	(12.71)	
Height (cm)	172.44	(9.97)	172.89	(9.96)	
Weight (kg)	90.82	(19.60)	90.58	(18.79)	
BMI	30.5	(5.94)	30.25	(5.53)	
Pulmonary disease	146	(10.70%)	110	(9.21%)	
Diabetes mellitus	134	(9.82%)	113	(9.46%)	
Depression	115	(8.42%)	77	(6.44%)	
Rheumatoid arthritis or other types of arthritis	112	(8.21%)	82	(6.86%)	
Diseases affecting the spine	299	(21.90%)	231	(19.33%)	
Congenital or developmental disease of the knee	573	(41.98%)	670	(56.07%)	*
No joint-related pre-existing conditions on the hip joint	829	(60.73%)	851	(71.21%)	*
No joint-related surgical history of the knee	587	(43.00%)	564	(47.20%)	*
Variables related to the surgery					
Surgery duration	73.27	(21.84)	67.80	(23.26)	
General complications requiring treatment	19	(1.39%)	6	(0.50%)	
Cardiovascular complication requiring treatment	2	(0.15%)	2	(0.17%)	
Other general complications requiring treatment	11	(0.81%)	2	(0.17%)	
Specific complications	8	(0.59%)	1	(0.08%)	

Note: The first column shows the mean for numeric variables and the count for categorical variables. The second column shows the standard deviation for numeric variables and the share in % for categorical variables in parentheses. A positive value in the absolute change in KOOS refers to an improvement from the pre-surgery KOOS to the 12-post-surgery KOOS. '*' denotes a significant difference between patients receiving rapid recovery and patients receiving conventional care with two-sided Welch's t-test (numeric or binary variables) and with two-sided Chi-Square test of independence (multinominal categorical variables) at $\alpha = 5\%$.

Table 1 shows the descriptive statistics for the patients on the rapid recovery care path and on the conventional care path. There are only minor differences in the pre-surgery KOOS and absolute change of pre-surgery and 12-month post-surgery for the two groups and neither is significant according to Welch's t-test ($\alpha = 5\%$). As we will select the 20 most important variables for the policy based on the causal forest (see table 6), we just report these in the descriptive statistics[6]. Education, congenital or developmental disease of the knee, no joint-related pre-existing conditions on the hip and no joint-related surgical history of the knee are significantly different in the sample of patients on the conventional care path and the rapid recovery care path, indicating that patients on the rapid recovery care path have a lower level of severity and complexity. This suggests that these affect the probability to be set on the rapid recovery care path or conventional care path and need to be controlled for. The causal forest and the double robust estimator need to be able to balance especially these variables. For the descriptive statistics on all variables see table 5

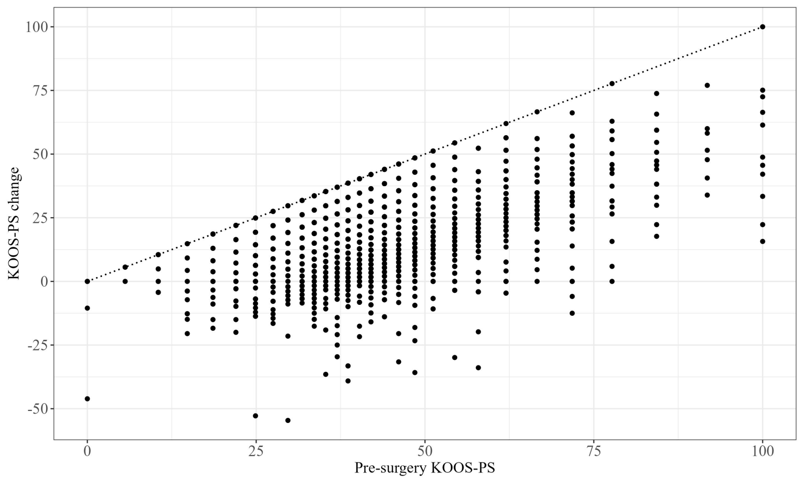

Figure 1: Scatter-plot of pre-surgery score and change

Note: A positive value in the absolute change in KOOS refers to an improvement from the pre-surgery KOOS to the 12-post-surgery KOOS.

Plot 1 shows the correlation between the pre-surgery KOOS and the absolute change of KOOS. A positive change denotes an improvement compared to the pre-surgery KOOS. Since the KOOS is a score from 0 (no impairment of functionality) to 100 (full impairment of functionality), there is a ceiling effect and there is a maximum possible improvement patients can have. The maximum improvement is visualised in the dotted line. This means that especially patients with low impairment of functionally have a small potential for improvement. Additionally, patients with high impairment of functionality are less likely to have a negative change of their KOOS. Therefore, by choosing absolute change as our the dependent variable and the outcome we aim to maximise in our policy tree, we focus more on patients with higher impairment of functionality.

Plot 2 shows the number of patients on the rapid recovery care path for each of the nine hospitals.[7] We observe a variability in the share of patients set on the rapid recovery path in the different hospitals. The maximum is at 71% and the minimum at 4%. This shows that hospital is an relevant control variable for estimating the ATE.

[6] For completeness we added categorical variables, if one category is among the important variables

[7] For data privacy reasons we cannot show the name and observations of the hospitals. The number of observations do not necessarily relate to the size of the hospital, it only refers to how successfull a hospital was in patient recruitment for the PROMoting Quality study

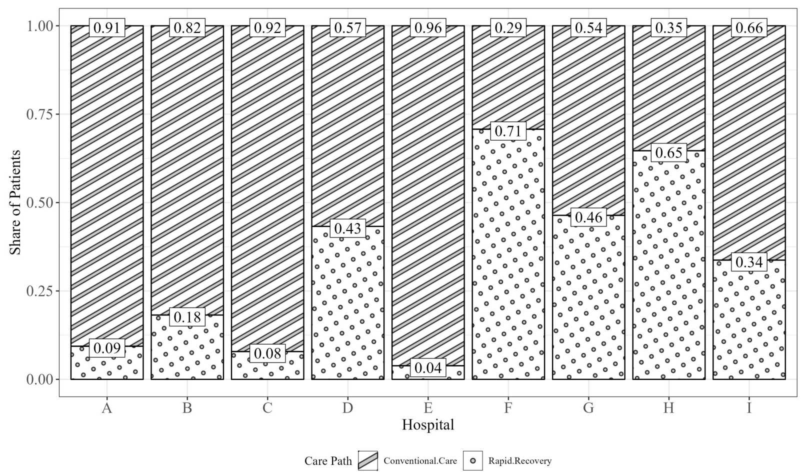

Figure 2: Share of rapid recovery patients per hospital

Note: This figure shows the share of patients on the rapid recovery and conventional care path in the nine hospitals. The hospital names are substituted with letters due to data privacy.

Average Treatment Effect

The causal forest and the double robust estimator suggest that patients on the rapid recovery care path improve their KOOS score by 1.58 points with a 95% confidence interval at 1.22 and 1.94 compared to patients on the conventional care path (see. 2). This suggests that setting all patients on the rapid recovery care path would - on average - increase the benefit the of patients.[8] We do not see a significant difference in the change of the pre-surgery and 12-month post-surgery KOOS for patients on the rapid recovery care path and conventional care path in the descriptive statistics. After controlling for patient characteristics we see a significant effect of the rapid recovery care path. This suggest in combination with the Figure 6 in the Appendix, that there exist patient characteristics that increase the probability for rapid recovery. The importance of confounders in the causal forest is shown in Table 6. The variable importance based on Wager & Athey (2018) shows how often a variable was chosen in the causal forest. Accordingly, BMI, age, pre-surgery KOOS, weight and height are the five most important confounders determining if a patient is set on the rapid recovery care path.

Table 2: Average Treatment Effect of the Rapid Recovery Care Path on KOOS Change

	ATE	**CI**
Knee Arthroplasty	1.58	[1.22, 1.94]

Note: Confidence bounds at $\alpha = 5\%$. The positive value in the ATE refers to a larger improvement from pre-surgery to 12-month-post-surgery KOOS for patients on the rapid recovery care path compared with patients on the conventional care path.

[8] This does not suggests that every individual patient benefits from the rapid recovery care path, as we can assume mixed bag effects.

Constrained and unconstrained Policy Tree

In this paragraph we show the policy tree for knee replacements and compare the welfare of different assignment rules. As the dependent variable in our study is the change of pre- to 12-month post-surgery KOOS, we refer to the KOOS change.

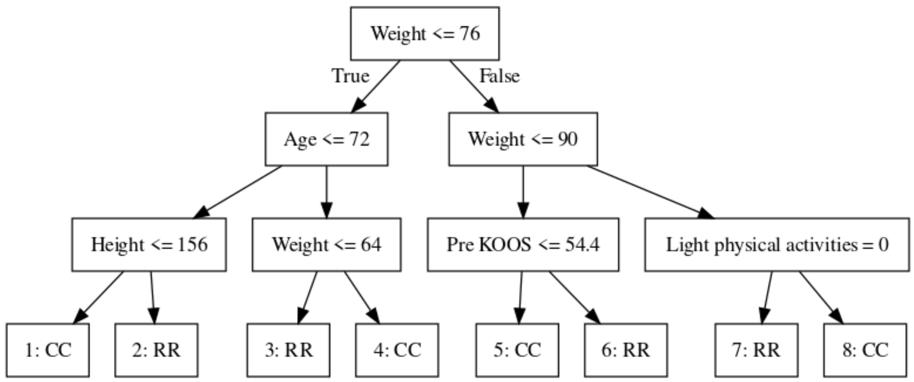

Figure 3: Unconstrained Policy tree: Knee Replacement

Note: The decision tree shows the decision criteria for an unconstrained policy tree with three layers. CC stands for the conventional care path and RR for the rapid recovery care path.

The unconstrained policy tree in Figure 3 splits patients on the three levels. This results in eight groups and eight CATEs. Following the assignments from the policy tree, patients in the groups with a positive point estimate should be set on the rapid recovery care path because the patient group benefits from the rapid recovery care path. Patients in the groups with a negative point estimate should be set on the conventional care path, because the patient group benefits from the conventional care path. As described in section 2.2, the policy tree creates groups that maximise welfare. Table A1 in the appendix shows the eight CATEs including confidence intervals and sample size for each group (i.e., policy tree node).

Patients weighing $\leq$ 76kg, younger or 72 years old and smaller or as tall as 156cm belong to group 1 and should be set on the conventional care path. This subgroub contains 33 patients. Its CATE has a point estimate of -1.88 and is insignificant at $\alpha = 5\%$ because of confidence intervals at -9.83 and 6.06. The other seven groups work equivalently.

The confusion matrix shows the comparison between the patient assignment based on the unconstrained policy tree and the status quo in Table 3. The policy tree sets 1,494 (58.36%) patients on the rapid recovery care path and 1,066 (41.64%) patients on the conventional care path. According to the optimal policy tree assignment, 713 patients should be set on the rapid recovery care path and are set on the rapid recovery care path in the sample. 584 patients are set on the conventional care path by the policy tree and follow it in the sample. Therefore, in the status quo, just 1,297 (50.66%) patients weren't reassigned and already were on their optimal post-surgery care path.

Table 3: Policy tree confusion matrix: Knee Arthropasty

N=2,560	**Treated by Policy Tree**	**Not Treated by Policy Tree**	**Sum (Share) in Status Quo**
Treated in Status Quo	713	482	1,195 (46.68%)
Not Treated in Status Quo	781	584	1,365 (53.32%)
Sum (Share) in Policy Tree	1,494 (58.36%)	1,066 (41.64%)	

Note: This table shows the confusion matrix of patients that are currently treated versus patients that should be treated according to the policy tree.

As discussed in section 1, there is a capacity constraint on how many patients can be mobilised within six hours after surgery, i.e., that can be set on the rapid recovery care path. The constraint policy tree creates subgroups that maximise the welfare while respecting set capacity constraint. As main scenario, we set the capacity constraint of the policy tree equal to the observed capacity constraint of our sample (46.68%). The constrained policy tree splits on other variables than the unconstrained policy tree. The resulting tree is shown in figure 4 and the CATE can be found in A2. The policy tree with capacity constraint works the same as the unconstrained policy tree. Patients weighing less than $90kg$ and less than $74kg$ and are younger or 70 years old are part of group 1 and should be set on the rapid recovery care path. This subgroub contains 236 patients and its CATE is significant at $\alpha = 5\%$ with a point estimate of 5.97. The other seven groups work equivalently. Following the constraint policy tree, $1,189$ (46.45%) patients should be set on the rapid recovery care path. The empirical capacity constraint was at 1195 (46.68%) on the rapid recovery care path, and therefore fulfilling the empirical capacity constraint.

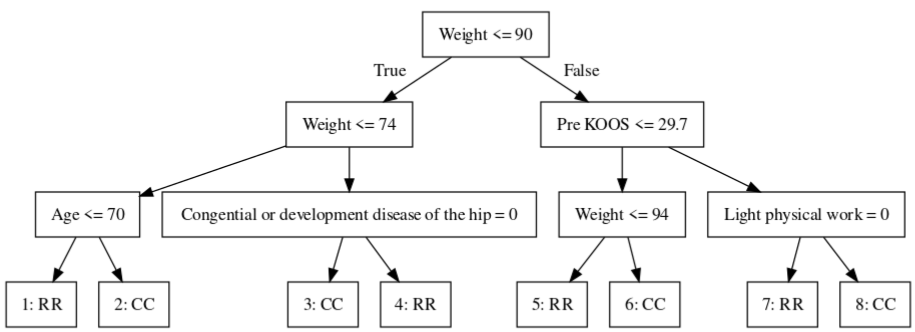

Figure 4: Constrained Policy tree: Knee Replacement

Note: The decision tree shows the decision criteria for a constrained policy tree with three layers. CC stands for the conventional care path and RR for the rapid recovery care path.

Using the policy tree with capacity constraint, we can estimate the change in KOOS for all theoretically possible capacity constraints, i.e., from 0 to 100% (see figure 5).[9] In Table 4 we report the welfare generated by the policies with different capacities. The unconstrained policy tree expects to generate a welfare of 20.13. The policy tree with the empirical capacity constraint is expected to generate a welfare of 20.02, demonstrating that the capacity constraint leads to 0.55% lower KOOS score than without a capacity constraint. As additional scenarios we included welfare at a capacity

[9]We had to exclude the highest and the lowest capacities because, this would result in unstable groups

constraint of 40% and 60% in Table 4. The confidence intervals show that the expected welfares of all four policy trees are significantly different from the observed welfare at $\alpha = 5\%$. The welfare of all patients following the rapid recovery care path is significantly higher than the observed welfare. Additionally, the point estimate of welfare is smaller than the point estimate of the unconstrained und constrained welfare, however insignificantly. This suggests that there is some evidence that not every patient benefits from the rapid recovery care path. The welfare, when all patients follow the conventional care path is significantly smaller then the observed welfare by reflecting the negative of the ATE.

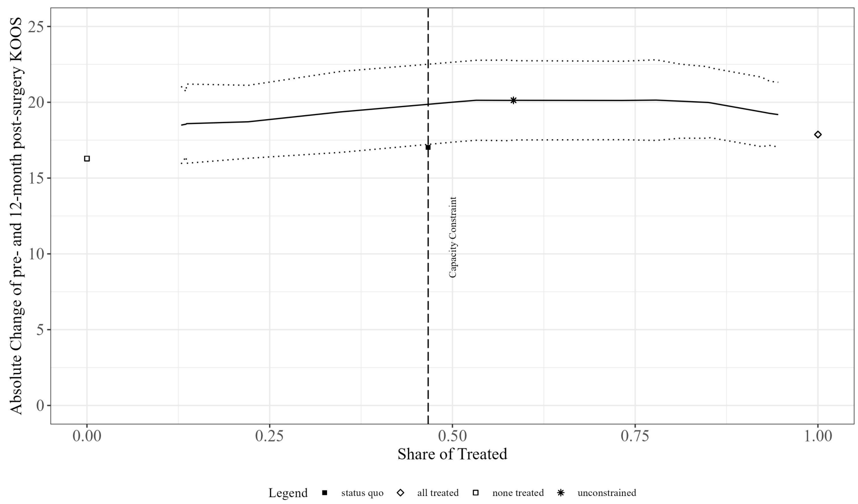

Figure 5: Welfare for the range of capacity constraints
Note: Confidence bounds at $\alpha = 5\%$. The positive value in the welfare refers to a larger improvement form the pre-surgery to the 12- month post-surgery KOOS. All observations are positive because it includes the effect of the knee replacement surgery.

Table 4: Welfare comparison

	Point Estimate	**Confidence Interval**	
Observed welfare	17.03		
Unconstrained Welfare	20.13	[17.53, 22.72]	*
Welfare with 60% capacity constraint	20.13	[17.51, 22.74]	*
Welfare with empirical capacity constraint	20.02	[17.39, 22.66]	*
Welfare with 40% capacity constraint	19.37	[16.7, 22.04]	
All patients on the rapid recovery care path	17.87	[17.51, 18.23]	*
No patients on the rapid recovery care path	16.29	[15.93, 16.65]	*

Note: Confidence bounds at $\alpha = 5\%$. The positive value in the welfare refers to a larger improvement form the pre-surgery KOOS to the 12-months post-surgery. "*" shows a significant difference with the observed welfare.

4 Discussion

We analyse the effect of the rapid recovery care path on the KOOS change from pre-surgery to 12-months post-surgery and develop optimal treatment assignment rules in the presence of capacity constraints (three scenarios). We utilise recently developed causal machine learning methods for the individual effect estimation (causal forest) and for the assignment rules (policy tree). We compare the welfare generated by the different possible policies.
We find that, on average, patients benefit from the rapid recovery care path with a 1.58 higher absolute change of the pre-surgery and 12-month post-surgery KOOS. The policy tree that maximises the average KOOS change selected more patients for the rapid recovery care path than the empirical capacity constraint would allow. The unconstrained policy expects an average KOOS change of 20.13. Enforcing the empirical capacity constraint results in a policy tree that estimates a higher absolute change than in the status quo with 20.02 versus 17.03. This implies that even without increasing (personnel) capacity, hospitals can increase their patients' expected functionality improvement by 17.56% by selecting the right patients for rapid recovery and by scheduling surgeries accordingly. Increasing the capacity to the optimum will only increase the KOOS change to 20.13. This suggests there are decreasing marginal returns if policy tree is used. Increasing the capacity even further, and setting all patients on the rapid recovery care path reduces the the welfare. This suggests that not every patient benefits from rapid recovery.
The developed policy tree can thus be used for the surgery scheduling process to select patients that benefit most from the rapid recovery care path. Patients weighing less than 76kg, younger than 72 and taller than 156cm benefit most from the rapid recovery care path in the unconstrained case. In the scenario with the empirical capacity constraint patients weighing between 90 and 94kg and a pre-surgery KOOS lower 29.7. Identified rapid recovery patients should be scheduled early, i.e., the surgery should start before 12.00 p.m. to ensure that patients can still be mobilised within 6h post-surgery. In our sample the surgery takes on average 70.72 minutes and in Berg et al. (2018) the earliest mobilisation is after three hours. Therefore, the patients need to be mobilised between 04.10 p.m. and 07.10 p.m. With a usual physiotherapy staff schedule from 8 a.m. to 04.30 p.m., mobilisation at 07.10 p.m. is unlikely. If we take into account that specialized nurses could also mobilise a patient, the nurses won‘t have time- to mobilise the patients during the switch between late- and night-shift.
Berg et al. (2020) analyses the effect of rapid recovery for knee replacements on patient reported outcomes, including KOOS. They show that rapid recovery has positive significant effects on four out of five KOOS subscales. The effects size is similar as our estimated effect between 1-2 points. However, there seems to be a strong selection of patients into the rapid recovery care path based on the pre-operative score, as there is a high significant difference in the pre-surgery KOOS. It is not clear what methods the authors used to control for patient characteristics, with very limited patient information. In our sample rapid recovery seems to be less dependent on the pre-surgery KOOS score, as we could not find a significant difference in our sample. This suggests that in our sample there are not as many selection criteria as in the sample used by Berg et al. (2020). With such a large difference in the pre-surgery KOOS it is also unclear whether common support is fulfilled. We show in Figure 6 that common support is fulfilled with estimated propensities far a way from 0 and 1, which allows us to control for patient characteristics more confidently.
To the best of our knowledge there are no studies using optimal assignment rules to select patients for the rapid recovery path. There are studies doing conventional subgroup analysis, whether rapid recovery is safe for specific patient groups Edwards et al. (2018); Berg et al. (2018). These studies

are not comparable to our approach, because we do not use predefined subgroubs to estimate outcomes.
Current applied paper using the optimal policy learning developed by Athey & Wager (2021) focus on targeting in several domains from product recommendation Wan et al. (2022), customer retention Ko et al. (2022), fundraising targets Cagala et al. (2021), coupon campaigns Langen & Huber (2023) and labour market training Athey & Palikot (2022). There are currently two studies in the broad field of health economics: Cassidy & Manski (2019) develop a decision-theoretic methodology for testing and treatment strategies for tuberculosis, without an application. McCullough & Shakya (2020) analyses the heterogeneous effects of health insurance on patient utility. McCullough & Shakya (2020) also build a policy tree. As it is based on the RCT Oregon Health Insurance Experiment, there is no confounding necessary and they do not enforce a capacity constraint. To the best of our knowledge there are no studies enforcing a capacity constraint.

Limitations

As all empirical studies, our study has limitations due to the available data and model assumptions. Regarding data, firstly, the limited sample size leads to underpowered subgroups and confidence intervals that are too large to show significant effects. This was especially visible for the CATEs with negative signs, i.e., subgroups for which conventional care is more beneficial than rapid recovery. This suggests that it is more difficult to construct subgroups for which the conventional care path yields significantly better results as compared to the rapid recovery care path. Similarly, there are four insignificant CATEs from the policy tree without a capacity constraint and four insignificant CATEs from the policy tree with the empirical capacity constraint. Additionally, the small sample size does not allow us to build confidence sets through cross-validation. Therefore, we do not know how stable the subgroups are and cannot evaluate the performance of the policy tree. Secondly, the sample might not be representative, because of a selection bias. There were many missing observations in the pre- and post-surgery KOOS. As this is the dependent variable, we had to exclude 550 observations (17.68%). This could lead to a selection bias, as we do not know why some patients did not provide information on their pre- and post-surgery KOOS. Additionally, patient data was obtained in a multi-center study including pre-selected nine German hospitals. The results might not represent the population as the hospitals all have specialised orthopedics departments.
We decided to define our single objective as maximising absolute change of pre-surgery and 12-month post-surgery KOOS. Alternative objectives could be relative change or the 12-month post-surgery KOOS. Choosing an alternative single objective or multiple objectives, based on a combination of single objectives, will not only change the effect estimates but will also change the assignment rules. By choosing absolute change we focus on patients with high impairment of functionality because patients with high impairment of functionality have a larger potential of improvement. By choosing the 12-month post-surgery KOOS as our objective we would focus on patients that reach the score for no impairment of functionality, which are patients with less pre-surgery impairment of functionality. Depending on the application, there are arguments focusing on either patients with low or high impairment of functionality. We decided to focus on patients with high impairment of functionality, because it is likely that patients with lower impairment, do need the knee replacement and could receive a conservative treatment. Additionally the literature uses change as the dependent variable.
Thirdly, in addition to mobilisation within six hours post-surgery, rapid recovery consists of two

pre-surgery measures, namely health literacy education and physiotherapy. In our data, we can only observe if a patient was mobilised within six hours post-surgery. Thus, in our conventional care group, patients initially selected for rapid recovery receiving both education and physiotherapy might be included. For these patients, we cannot isolate the effects of both pre-surgery measures on the 12-month KOOS change. Still, it can be argued that these pre-surgery measures are to further improve patients health state. Thus, this limitation might result in an underestimation of the ATE. In other words, if we could identify and exclude pre-surgery rapid recovery patients that ended up receiving conventional care, our results might be even more significant.
Regarding model assumptions, the estimates might be biased due to failing of the conditional independence assumption. More concretely, there are information missing on patient motivation. The conditional independence assumptions is likely to fail, if patients with a higher motivation opt into rapid recovery and these patients additionally are more motivated in the rehabilitation program. Those patients are most likely to have a higher improvement. This would then lead to biased (C)ATEs. Still, we can argue that also patients motivated to participate in a rapid recovery program are limited by hospitals' capacity constraint and surgeons' willingness to accept their request.
Lastly, in our the data, the number and share of patients with complications (readmissions and revisions) is very small. If surgery outcome was more heterogeneous, it would be possible to add the estimated probability for a complication as a decision, to additionally schedule the post-surgery path based on patients' risk for complications.

5 Conclusion

This study finds that the rapid recovery care path significantly improves the average absolute functionality change for knee replacement patients. We use an optimal assignment method to show that the best assignment rules would require more patients to be set on the rapid recovery care path than observed in our sample. The policy tree identifies subgroups that should receive the rapid recovery with priority to maximise expected positive functionality change under the observed capacity constraint. Correspondingly, our results show that hospitals can increase their patients' expected health gains even without increasing their capacity. This can be achieved by selecting the patients to be assigned to rapid recovery as identified by the policy tree. We find that health outcome changes can be increased on average from 17.03 to 19.25 on the KOOS scale without increasing capacity using optimal assignment rules selecting patients for rapid recovery with characteristics linked to higher health gains. In a clinical setting, planning and scheduling of surgeries would have to align with this prioritisation to unlock potential healthcare quality gains. Surgery planning and scheduling software and clinical decision support systems for post-surgery care plans should thus incorporate algorithms such as the one presented here.

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A Appendix

A.1 Descriptive Statistics

Table 5: Descriptive Statistics - All Variables

	Conventional Care		Rapid Recovery		
	N=1,365		N=1,195		
Dependent Variable					
KOOS change	16.98	(14.60)	17.08	(15.10)	
Socio-demographic Variables					
Gender					
Male	635	(46.52%)	555	(46.44%)	
Female	729	(53.41%)	631	(52.80%)	
Other	1	(0.07%)	9	(0.75%)	
Job					
Job-seeker	16	(1.17%)	9	(0.75%)	
Unable to work due to arthrosis	105	(7.69%)	102	(8.54%)	
Unable to work due to a condition other than arthritis	55	(4.03%)	31	(2.59%)	
Voluntarily not working	780	(57.14%)	703	(58.83%)	
Employed part-time	118	(8.64%)	110	(9.21%)	
Employed ful-time	291	(21.32%)	240	(20.08%)	
Job effort					
I cannot judge that	130	(9.52%)	112	(9.37%)	
Predominantly sitting activities	512	(37.51%)	466	(39.00%)	
Light physical activities	237	(17.36%)	231	(19.33%)	
Medium-heavy physical activities	319	(23.37%)	264	(22.09%)	
Heavy physical activities	167	(12.23%)	122	(10.21%)	
Education					*
No school-leaving qualification	11	(0.81%)	1	(0.08%)	
Primary school	255	(18.68%)	184	(15.40%)	
Secondary school	804	(58.90%)	704	(58.91%)	
University	295	(21.61%)	306	(25.61%)	
Age	65.78	(9.10)	66.28	(9.57)	
Living situation					
Other	7	(0.51%)	10	(0.84%)	
I live alone	268	(19.63%)	204	(17.07%)	
I live in an institutional setting	13	(0.95%)	3	(0.25%)	
I live with my family	1,077	(78.90%)	978	(81.84%)	
Medical Variables					
Pre-surgery KOOS (0-100)	43.52	(12.95)	42.51	(12.71)	
Height (cm)	172.44	(9.97)	172.89	(9.96)	
Weight (kg)	90.82	(19.60)	90.58	(18.79)	
BMI	30.50	(5.94)	30.25	(5.53)	
Heart disease					

No	1,200	(87.91%)	1,059	(88.62%)	
Yes	165	(12.09%)	136	(11.38%)	
Hypertension					
No	594	(43.52%)	524	(43.85%)	
Yes	771	(56.48%)	671	(56.15%)	
Consequences of a stroke					
No	1331	(97.51%)	1,174	(98.24%)	
Yes	34	(2.49%)	21	(1.76%)	
Pain in the legs due to poor circulation					
No	1301	(95.31%)	1,142	(95.56%)	
Yes	64	(4.69%)	53	(4.44%)	
Pulmonary disease					
No	1,219	(89.30%)	1,085	(90.79%)	
Yes	146	(10.70%)	110	(9.21%)	
Diabetes mellitus					
No	1,231	(90.18%)	1,082	(90.54%)	
Yes	134	(9.82%)	113	(9.46%)	
Disease of the nervous system					
No	1,319	(96.63%)	1,164	(97.41%)	
Yes	46	(3.37%)	31	(2.59%)	
Cancer (in the past 5 years)					
No	1,287	(94.29%)	1,138	(95.23%)	
Yes	78	(5.71%)	57	(4.77%)	
Depression					*
No	1,250	(91.58%)	1,118	(93.56%)	
Yes	115	(8.42%)	77	(6.44%)	
Rheumatoid arthritis or other types of arthritis					
No	1,253	(91.79%)	1,113	(93.14%)	
Yes	112	(8.21%)	82	(6.86%)	
Diseases affecting the spine					
No	1,066	(78.10%)	9,64	(80.67%)	
Yes	299	(21.90%)	231	(19.33%)	
Congenital or developmental disease of the hip joint					
No	1,333	(97.66%)	1,157	(96.82%)	
Yes	32	(2.34%)	38	(3.18%)	
Prior joint-replacement on the knee					
No	1,232	(90.26%)	1,069	(89.46%)	
Yes	133	(9.74%)	126	(10.54%)	
Prior osteotomy on the hip joint					
No	1,362	(99.78%)	1,192	(99.75%)	
Yes	3	(0.22%)	3	(0.25%)	
Prior osteotomy on the knee					
No	1,354	(99.19%)	1,184	(99.08%)	
Yes	11	(0.81%)	11	(0.92%)	
Congenital or developmental disease of the knee					*
No	792	(58.02%)	525	(43.93%)	

Yes	573	(41.98%)	670	(56.07%)	
No joint-related pre-existing conditions on the hip joint					
No	536	(39.27%)	344	(28.79%)	
Yes	829	(60.73%)	851	(71.21%)	*
No joint-related pre-existing conditions on the knee					
No	1,025	(75.09%)	892	(74.64%)	
Yes	340	(24.91%)	303	(25.36%)	
Prior joint-replacement on the hip joint					
No	1,276	(93.48%)	1,123	(93.97%)	
Yes	89	(6.52%)	72	(6.03%)	
Prior reconstruction of the knee ligaments					
No	1,307	(95.75%)	1,153	(96.49%)	
Yes	58	(4.25%)	42	(3.51%)	
Other arthroscopic procedures on the knee					*
No	1,035	(75.82%)	860	(71.97%)	
Yes	330	(24.18%)	335	(28.03%)	
No joint-related surgical history of the hip joint					*
No	516	(37.8%)	336	(28.12%)	
Yes	849	(62.20%)	859	(71.88%)	
No joint-related surgical history of the knee					*
No	778	(57.00%)	631	(52.80%)	
Yes	587	(43.00%)	564	(47.20%)	
Variables related to the surgery					
Surgery duration	73.27	(21.84)	67.8	(23.26)	
General complications requiring treatment					*
No	1,346	(98.61%)	1,189	(99.50%)	
Yes	19	(1.39%)	6	(0.50%)	
Cardiovascular complication requiring treatment					
No	1,363	(99.85%)	1,193	(99.83%)	
Yes	2	(0.15%)	2	(0.17%)	
Other general complications requiring treatment					*
No	1,354	(99.19%)	1,193	(99.83%)	
Yes	11	(0.81%)	2	(0.17%)	
Specific complications					*
No	1,357	(99.41%)	1,194	(99.92%)	
Yes	8	(0.59%)	1	(0.08%)	

Note: The first column shows the mean for numeric variables and the count for categorical variables. The second column shows the standard deviation for numeric variables and the share in % for categorical variables in parentheses. A positive value in the absolute change in KOOS refers to an improvement from the pre-surgery KOOS to the 12-post-surgery KOOS. '*' denotes a significant difference between patients receiving rapid recovery and patients receiving conventional care with two-sided Welch's t-test (numeric or binary variables) and with two-sided Chi-Square test of independence (multinominal categorical variables) at $\alpha = 5\%$.

A.2 Variable Importance

Table 6: Variable importance

Variable Importance	Name	Included in policy tree
0.1539	BMI	
0.1322	Age	X
0.1310	Pre-surgery KOOS	X
0.1300	Weight	X
0.0844	Height	X
0.0521	Depression	X
0.0363	Light physical activities	X
0.0190	Predominantly sitting activities	X
0.0171	Heavy physical activities	X
0.0158	Pulmonary disease	X
0.0145	Congenital or developmental disease of the knee	X
0.0143	Hospital H	
0.0134	Other arthroscopic procedures on the knee	X
0.0125	Diabetes mellitus	X
0.0119	Diseases affecting the spine	X
0.0100	Secondary school	X
0.0095	Female	X
0.0095	No joint-related pre-existing conditions on the hip joint	X
0.0094	Rheumatoid arthritis or other types of arthritis	X
0.0089	Hospital I	
0.0085	No joint-related surgical history of the knee	X
0.0080	Hospital D	
0.0080	Heart disease	X
0.0073	I live with my family	X
0.0071	University	
0.0069	No joint-related pre-existing conditions on the knee	
0.0068	Hypertension	
0.0063	No joint-related surgical history of the hip joint	
0.0060	Cancer (in the past 5 years)	
0.0058	Voluntarily not working	
0.0049	Prior joint-replacement on the knee	
0.0049	Unable to work due to arthrosis	
0.0048	Medium-heavy physical activities	
0.0048	Prior joint-replacement on the hip joint	
0.0038	I live alone	
0.0038	Employed part-time	
0.0034	Employed full-time	
0.0033	Pre-existing conditions of the knee	
0.0031	Hospital F	
0.0027	Congenital or developmental disease of the hip joint	

0.0012	Prior reconstruction of the knee ligaments
0.0011	Hospital G
0.0009	Unable to work due to a condition other than arthritis
0.0008	Pain in the legs due to poor circulation
0.0000	Surgery duration
0.0000	Consequences of a stroke
0.0000	Hospital A
0.0000	Hospital C
0.0000	General complications requiring treatment
0.0000	Cardiovascular complication requiring treatment
0.0000	Other general complications requiring treatment
0.0000	Specific complications requiring treatment
0.0000	Disease of the nervous system
0.0000	Prior joint-replacement on the knee
0.0000	Hospital B
0.0000	Prior osteotomy on the knee
0.0000	Prior osteosynthesis on the knee
0.0000	Prior reconstruction of the knee ligaments
0.0000	Other arthroscopic procedures on the knee
0.0000	Congenital or developmental disease of the knee
0.0000	Hospital E
0.0000	Other Gender
0.0000	Prior osteotomy on the hip joint
0.0000	I live in an institutional setting
0.0000	No school-leaving qualification

Note: The table shows the variable importance for all confounders based on (Wager & Athey, 2018). Variables are also indicated if they are used in the policy tree. There is one category left out due to dummyfication of each categorical variables.

A.3 Test for Common Support

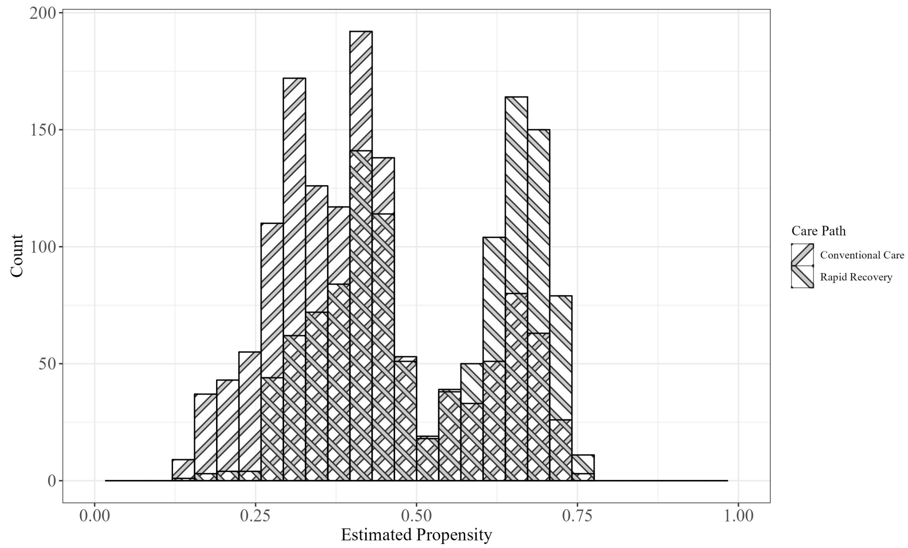

Figure 6: Common support of estimated propensity scores

Note: The scores should be > 0 and < 1.

A.4 Conditional Average Treatments Effects of the Policy Trees

Table A1: Conditional Average Treatment Effects of the Rapid Recovery Care Path on KOOS Improvement with unconstrained Policy Tree

Point Estimate	**CI**	**Sample Size**	**Node Number**	**Action**
-2.61	[-6.41, 1.19]	157	8	CC
4.31	[2.62, 6]	1024	7	RR
4.54	[-3.22, 12.30]	86	6	RR
-1.91	[-3.73, -0.09]	685	5	CC
-5.79	[-9.57, -2.01]	191	4	CC
5.16	[-0.82, 11.14]	81	3	RR
5.67	[2.59, 8.75]	303	2	RR
-1.88	[-9.83, 6.06]	33	1	CC

*Note:*Confidence bounds at $\alpha = 5\%$. The positive value in the CATE refers to a larger improvement from pre-surgery to 12-month-post-surgery KOOS for patients on the rapid recovery care path compared with patients on the conventional care path.

Table A2: Conditional Average Treatment Effects of the Rapid Recovery Care Path on KOOS Improvement with constrained Policy Tree

Point Estimate	**CI**	**Sample Size**	**Node Number**	**Action**
-3.46	[-7.56, 0.63]	134	8	CC
4.75	[2.99, 6.51]	934	7	RR
-4.24	[-10.23, 1.74]	89	6	CC
16.16	[4.52, 27.79]	24	5	RR
12.95	[-3.19, 29.09]	31	4	RR
-1.85	[-3.60, -0.11]	829	3	CC
-0.78	[-3.88, 2.31]	283	2	CC
5.97	[2.52, 9.42]	236	1	RR

Note: Confidence bounds at $\alpha = 5\%$. The positive value in the CATE refers to a larger improvement from pre-surgery to 12-month-post-surgery KOOS for patients on the rapid recovery care path compared with patients on the conventional care path.